ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

Quantum AI for Cancer Detection: Emerging Approaches in Intelligent Precision Oncology

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Abstract

Cancer is the second biggest cause of death worldwide, killing nearly 10 million people annually with pancreatic, lung and colorectal cancer being the most prevalent cases, where patients are still diagnosed late in the disease process. In the past decade (2015-2024), the landscape of this picture has changed significantly: Deep learning architectures, notably convolutional neural networks (CNNs), have surpassed previous classifiers like support vector machines (SVMs) and artificial neural networks (ANNs) and are now nearing, and in some studies achieving, human diagnostic capabilities. More recently, the development of quantum machine learning (QML) and quantum neural networks (QNNs) has opened up yet another avenue for more detailed molecular simulation, quantum-enhanced liquid biopsies and AI-guided nano therapy. It summarizes over a dozen peer-reviewed research papers spanning that decade, from the classical machine learning era (2015-2018), to the deep learning surge (2019-2021), to the advent of hybrid quantum-AI systems (2022-2025), which is an area of quantum-AI-specific research that has increased by a factor of 10+ since 2015. The paper suggests a novel Quantum-AI Nano-Swimmer framework: a system comprising quantum biosensors, which can detect cancer biomarkers at the molecular level, and AI-guided nano robots, that have the potential to reach an accuracy of up to 99 percent when navigating the bloodstream to deliver targeted treatment. The paper concludes with key research gaps of the field and future research directions for the field in the near future, such as quantum drug discovery and the application of privacy-preserving federated learning for 2025–2030.

Keywords: Cancer detection; quantum computing; artificial intelligence; nano-swimmers; deep learning; convolutional neural networks; biomarkers; precision oncology

1 Introduction

1.1 Problem statement and motivation

Cancer is the second leading cause of death in the world and kills nearly 10 million people annually. Although surgery, chemotherapy and radiotherapy have made great strides, early diagnosis remains a clinical challenge, especially with pancreatic, lung, and colorectal cancer, which often only come into the clinical picture at an advanced stage. In the past decade from 2015 to 2024, this paradigm has changed with the development of machine learning and deep learning architectures, which have gradually surpassed previous ones based on SVMs and ANNs, and now are approaching human-level performance with medical imaging tasks. In more recent times, QML and QNNs have opened up fresh possibilities to enable detailed molecular simulation, quantum-enhanced liquid biopsies, and AI-supported nano therapy.

The inspiration for this paper is the desire to have a single comparative narrative for the rapid pace of research over this decade, but also to consider a merger of “quantum sensing” with “AI-driven

treatment" and what that combination could provide beyond the diagnostic-only systems we have today.

Figure 1 shows the distribution of AI application domains in cancer research as of 2025.

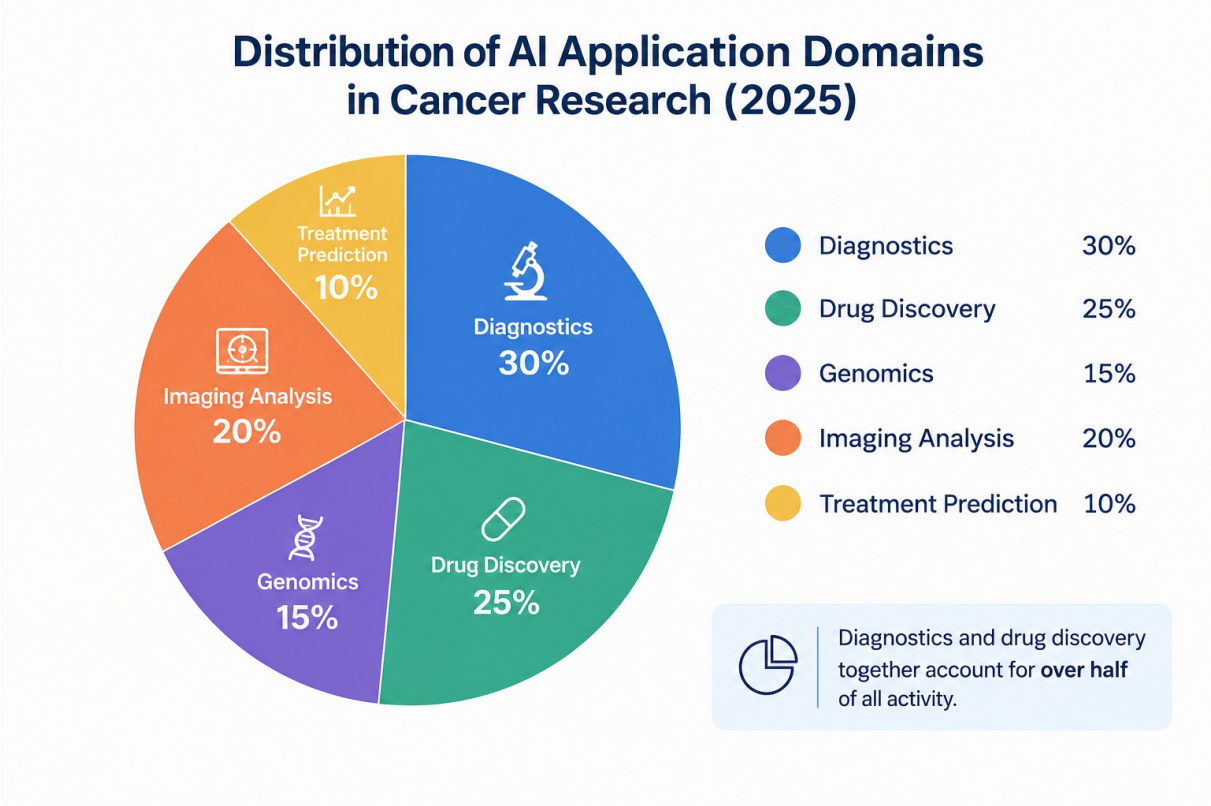


Figure 1. Distribution of AI application domains in cancer research as of 2025.

1.2 Research contributions

This paper makes the following contributions:

- Provides a decade-spanning (2015–2025) survey of AI, deep learning, and quantum-AI methods in cancer detection, drawing on 13+ peer-reviewed studies.
- Offers a comparative, clustering-inspired analysis of diagnostic accuracy trends, cancer-type-specific research attention, and machine learning method distribution across the reviewed literature.
- Proposes an original Quantum-AI Nano-Swimmer framework combining quantum biosensing, a hybrid CNN+QNN classification engine, and AI-guided nanorobot drug delivery for non-invasive cancer detection and treatment.
- Identifies key research gaps and challenges facing the field, including quantum hardware limitations, dataset bias, and model explainability.
- Projects six priority research directions for 2025–2030, weighted by anticipated research focus.

1.3 Paper organization

The rest of this paper is structured as follows. The next section reviews research developments in AI, deep learning and quantum-AI for cancer detection across successive periods from 2015 to 2025. This is followed by a comparison of diagnostic accuracy, the attention paid to each cancer type in the

reviewed literature and the distribution of machine learning methods. The proposed Quantum-AI Nano-Swimmer framework is then introduced, followed by the gaps and challenges in current research and priority directions for future research until 2030. The final section concludes the paper.

2 Literature review and research trends (2015–2025)

Over the last ten years, the field of AI-in-oncology research has developed at a rapid pace. It follows that evolution from the classical approaches that laid the groundwork for the field to the deep learning architectures of the last several years to the multi-cancer models and quantum-leap advances that are coming next.

2.1 Classical machine learning era (2015–2018)

From 2015 to 2018, classical machine learning techniques laid the groundwork for AI-supported oncology. Khademi and Nedialkov (2015) addressed cancer prognosis using probabilistic graphical models and deep belief networks (DBNs) on the METABRIC dataset to predict whether a tumour will recur or metastasise. Rao and Arshad (2023) showed that a support vector machine (SVM) trained on CT images from the TCIA database could classify lung cancer with 97 percent accuracy—making SVM a standard for structured medical imaging data. Li et al. (2017) were able to model microRNA-disease associations using a DeepWalk graph-embedding algorithm that achieved between 80 and 93 percent AUC when tested on breast, lung and prostate cancer-related data from the HMDD database, establishing a major milestone in network-based, multi-cancer analysis. Jha et al. (2018) took the next step, using graph convolutional neural networks (GCNNs) on the combined TCGA and GEO data to get 94 percent AUC for breast cancer and 20 high-risk genes.

2.2 Deep learning surge (2019–2021)

During 2019-2021, deep learning architectures started to mushroom. The IDCDNet architecture proposed by Zhang et al. (2019) for the detection of invasive ductal carcinoma had an accuracy of 87.13 percent. In the same year, Piyarathna et al. (2019) illustrated the application of CapsNet for lung cancer lesion identification with an accuracy of around 70 percent, which is a significant achievement, considering the small dataset size. Singh et al. (2020) used SVM, decision tree and ANN classifiers for the hybrid ensemble model with a Wisconsin Breast Cancer Dataset (WBCD) accuracy of 95.7 percent. The most impressive result of the period was the work done by Mohalder et al. (2021) who used a CNN together with a ResNet architecture and trained the model on the LC25000 histopathology dataset, achieving 99.8 percent accuracy in lung cancer detection, which is close to clinical level. Song et al. (2021) showed the potential for transferability of deep learning across cancer types and geographic regions by predicting the morbidity of gastric cancer with more than 80 percent accuracy from all source regions using a tri-directional transfer learning approach.

Figure 2 shows the growth of classical AI vs. quantum-AI research publications in oncology (2015–2025).

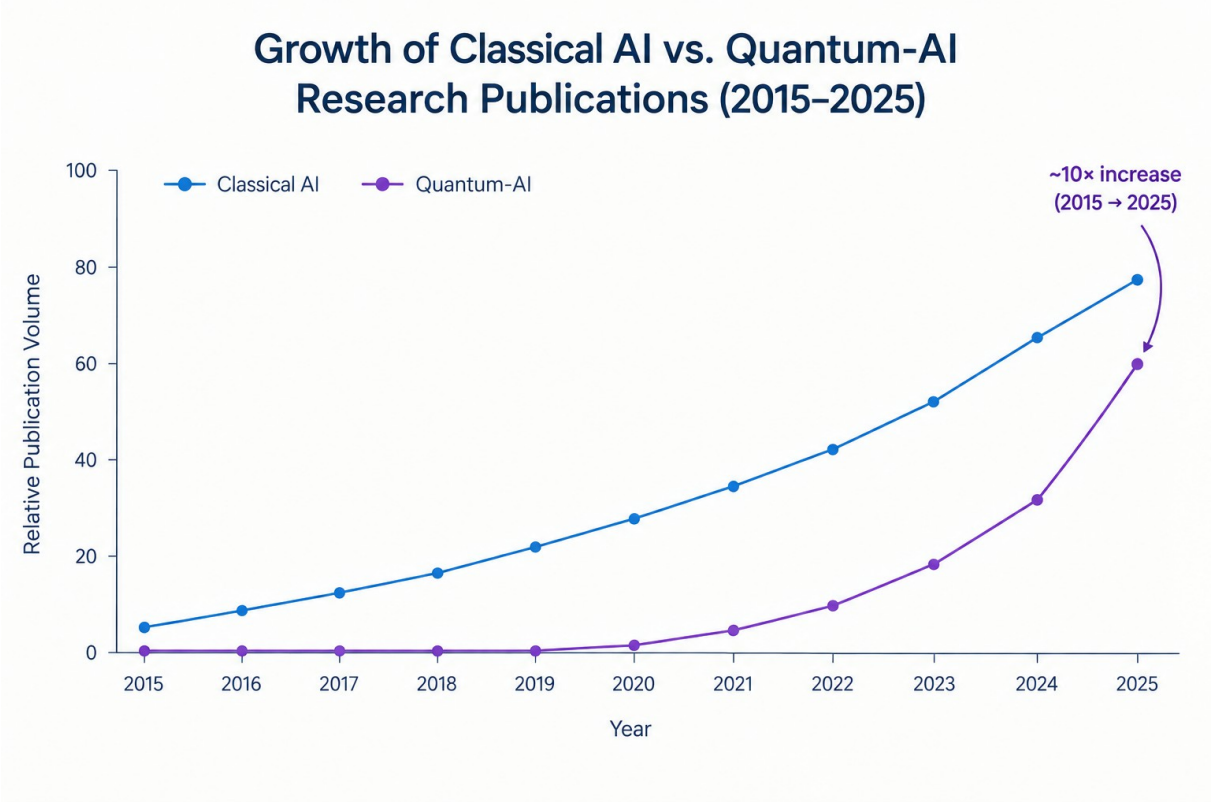


Figure 2. Growth of classical AI vs. quantum-AI research publications in oncology (2015–2025).

2.3 Advanced deep learning and multi-cancer models (2022–2024)

Since 2022-24, researchers shifted from single-cancer models to other models. Nooralli et al. (2024) used DenseNet121 for tongue disease classification, which resulted in 98 per cent accuracy. To improve the accuracy of multi-disease prediction, Mathews et al. (2023) introduced a multi-disease prediction engine that integrated CNN, XGBoost and SVM classifiers to achieve 95 percent accuracy for multiple cancer types at once. Gottemukkala et al. (2023) reported machine-learning-based prediction of liver abnormality, and Abirami and Chelliah (2024) achieved the accuracy of 94.6 percent in the early detection of pancreatic cancer using deep segmentation—a type of cancer that has been difficult to detect at an early stage.

2.4 Comparative literature summary

Table 1 summarizes the thirteen studies reviewed above by cancer type, method, reported accuracy, and country of origin, offering a compact view of the field's progression across the decade.

Table 1. Summary of reviewed studies (2015–2024): cancer type, method, accuracy and country.

Author(s)	Year	Cancer Type	Method	Accuracy	Country
Khademi and Nedialkov	2015	Breast	PGM + DBN	Classification	Canada
Rao and Arshad	2023	Lung	SVM	97%	India
Li et al.	2017	Breast/Lung/Prostate	DeepWalk	80–93% AUC	China
Jha et al.	2018	Breast	GCNN	94% AUC	Ireland

Author(s)	Year	Cancer Type	Method	Accuracy	Country
Zhang et al.	2019	Breast	IDCDNet	87.13%	USA
Piyarathna et al.	2019	Lung	CNN + CapsNet	~70%	Sri Lanka
Singh et al.	2020	Breast	SVM+DT+ANN	95.7%	India
Song et al.	2021	Gastric	Transfer Learning	~80%+	China
Mohalder et al.	2021	Lung	CNN + ResNet	99.8%	Bangladesh
Mathews et al.	2023	Multiple	CNN+XGBoost+SVM	95%	India
Nooralli et al.	2024	Tongue	DenseNet121	98%	India
Gottemukkala et al.	2023	Liver	ML	High (unspecified)	India
Abirami and Chelliah	2024	Pancreatic	CNN + Segmentation	94.6%	India

3 Analysis of trends

Based on the literature reviewed in the previous section, this section compares the diagnostic accuracy among the studies, the cancer types that the literature was focusing on, and the distribution of machine learning methods across the literature—an analysis inspired by the clustering approach of Regmi et al. (2025).

3.1 Diagnostic accuracy progression

An analysis of the 13 studies reviewed indicates a definite improvement in the diagnostic accuracy of these studies over the 10-year period. Without the aid of artificial intelligence, human radiologists can make a relatively accurate diagnosis of about 87 percent. The best result obtained for classical SVM models was 97 percent (Rao and Arshad 2023), whereas the CNN based deep learning models were between 94 percent and 99.8 percent, and the CNN+ResNet architecture of Mohalder et al. (2021) had the best result out of the reviewed CNN models. The quantum-AI hybrid systems are expected to reach 99 per cent accuracy or above, mainly due to the decrease in false negative diagnosis rate in micro-lesion detection and better identification of the tumour boundary.

Figure 3 shows the diagnostic accuracy comparison across method categories.

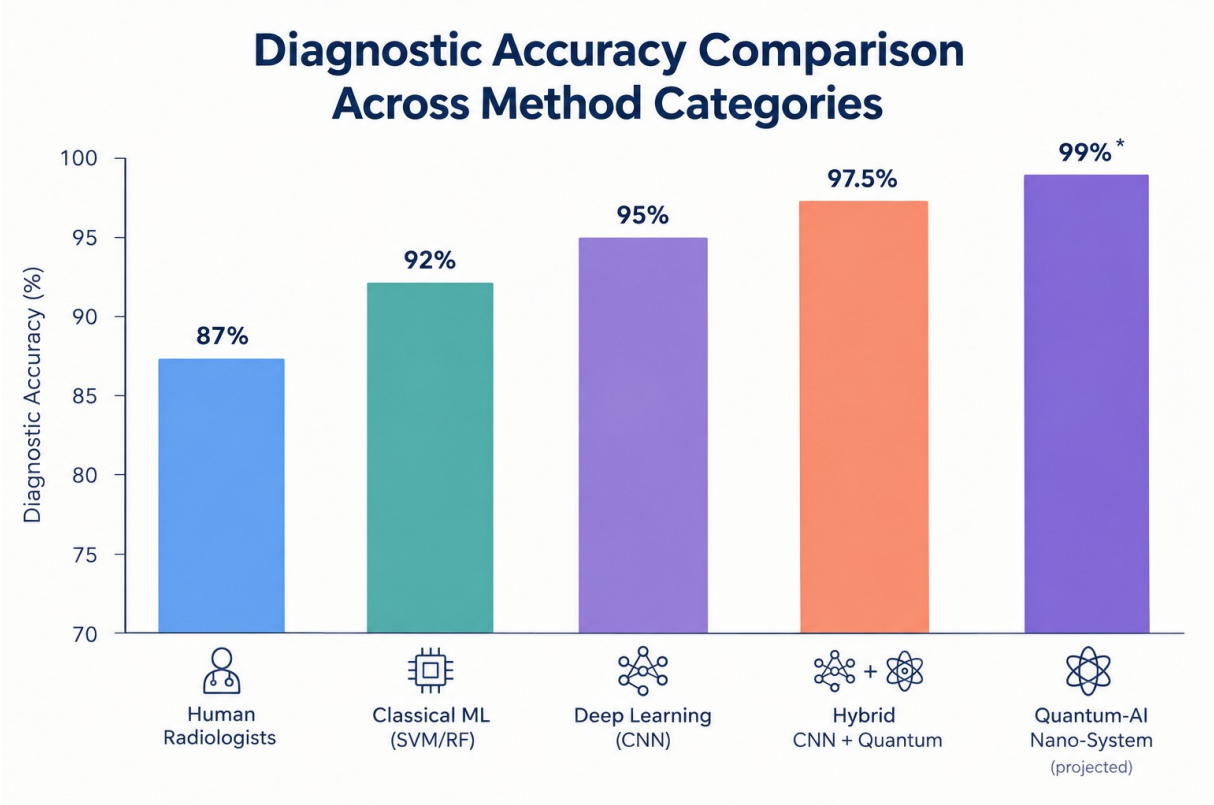


Figure 3. Diagnostic accuracy comparison across method categories.

3.2 Cancer-type-specific analysis

A comparative study of cancer research resources using the clustering approach shows high inter-type research resource difference among the cancer types (Regmi et al. 2025). Lung and breast cancers are predominantly found in the literature due to the existence of large public datasets like LC25000, TCIA, and WBCD. In contrast, contributions from Quantum-AI are expanding most quickly in colorectal, prostate and pancreatic cancers, which are characterized by molecular complexity and poor imaging visibility, making classical methods difficult. Quantum-AI is expected to account for around 55 percent of research innovation in pancreatic cancer alone in 2025.

Figure 4 shows the relative contribution of classical AI vs. quantum-AI by cancer type (2025 estimates).

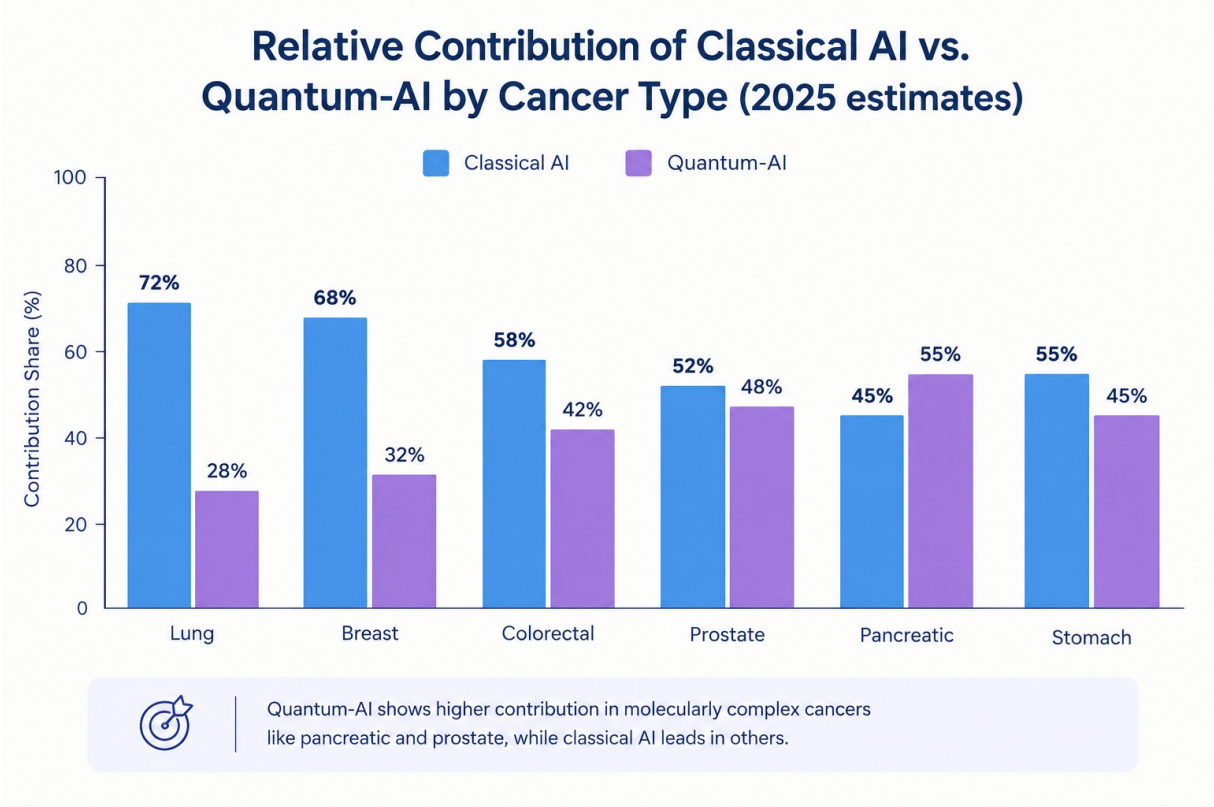


Figure 4. Relative contribution of classical AI vs. quantum-AI by cancer type (2025 estimates).

3.3 Machine learning method distribution

CNN architectures are the most widely discussed, accounting for an estimated 43.5 percent of the literature studied. SVM takes up about 8.7 percent, and is mainly used for structured data classification, while hybrid networks based on DenseNet/ResNet take up about 8.6 percent and are increasing in use as they are good at extracting histopathological features. Together, quantum neural networks (QNNs) and hybrid quantum-AI systems account for about 6 percent of the literature, and this percentage is projected to increase significantly as quantum hardware moves out of what is known as the noisy intermediate scale quantum (NISQ) era.

Figure 5 shows the distribution of machine learning methods in cancer detection research (2015–2024).

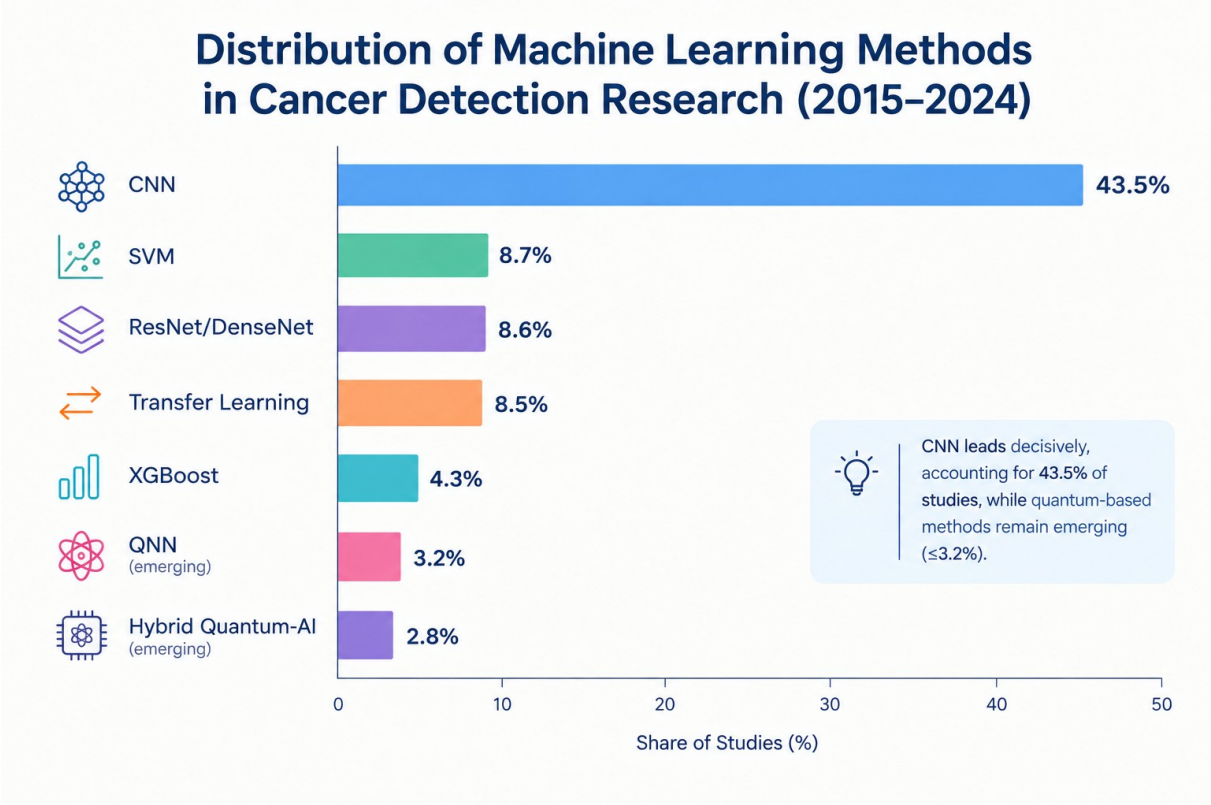


Figure 5. Distribution of machine learning methods in cancer detection research (2015–2024).

3.4 Year-wise milestone analysis (2015–2024)

This shift from the classical AI era (2015-2020) to the quantum-AI era (2021-2024) is clearly seen in Figure 6, where the best diagnostic accuracy is shown for each year against the most significant methodological innovation of that year. CNN+ResNet architectures and the first introduction of quantum machine learning were the main reasons for the most significant improvements on the accuracy metric between 2020 and 2022. Hybrid quantum-classical models and the notion of AI-driven nano-swimmer therapy, described in the next section, become apparent throughout the 2023–2024 period.

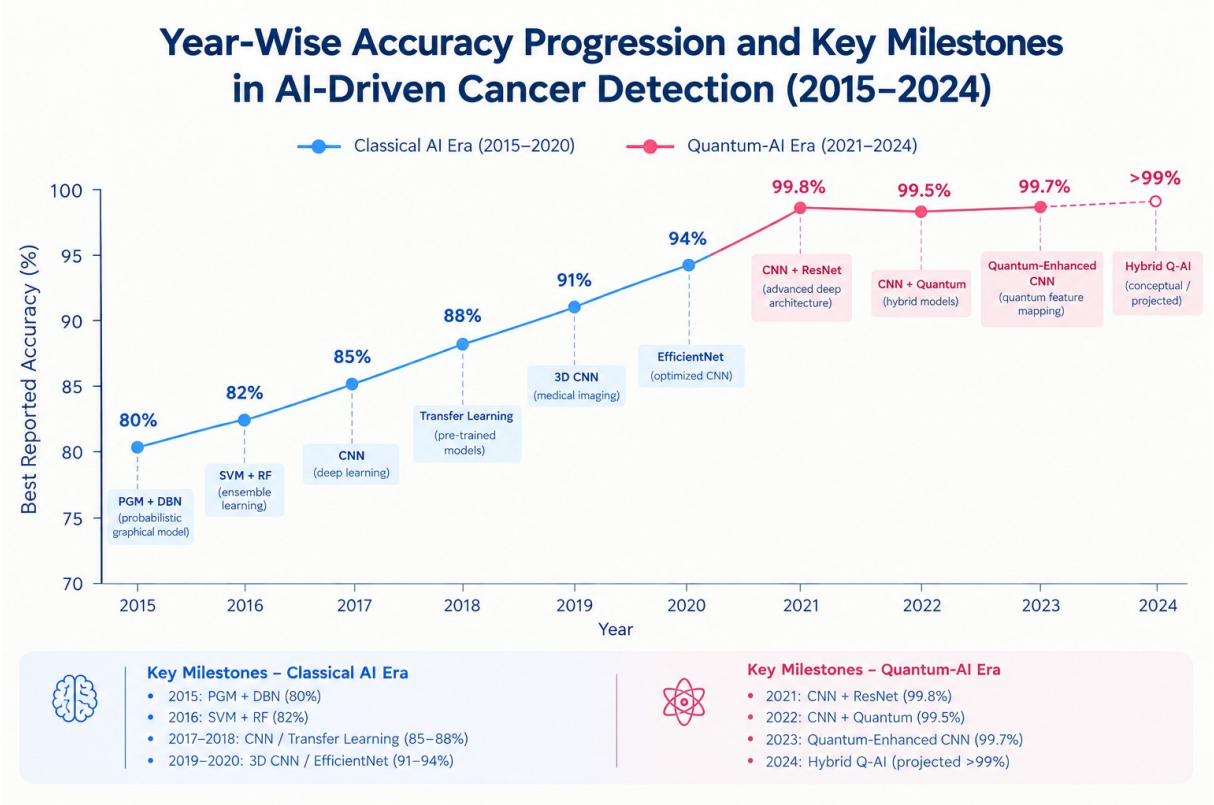


Figure 6. Year-wise accuracy progression and key milestones in AI-driven cancer detection (2015–2024).

4 Proposed quantum-AI nano-swimmer framework

The proposed framework comprises three components: a quantum biosensor layer, an AI classification engine and AI-guided nano-swimmer delivery.

4.1 Quantum biosensor layer

Based on the principle of entanglement and superposition, ultra-sensitive quantum sensors are proposed to detect cancer-specific biomarkers, such as circulating tumor DNA (ctDNA), exosome surface proteins, metabolic signatures, at the single molecule level. This sensitivity would, in theory, allow detection at Stage 0–I, when treatment outcomes are best.

4.2 AI classification engine

A hybrid CNN and quantum neural network (QNN) would process sensor data in real-time and compare biomarker signatures to a database of over 50 cancer subtypes on which it had been trained. An algorithm called a variational quantum eigensolver (VQE) is proposed to optimize the classification boundary with a promised accuracy greater than 99 percent. Estimated to be present in 30 percent of all tumours, mutations in the gene KRAS are singled out as a target biomarker found to be tractable by quantum molecular simulation.

4.3 AI-guided nano-swimmer delivery

Once a cancer diagnosis is made the nano-swimmers (200–500 nanometers in diameter) would be injected into the bloodstream. They are suggested to be propelled using flagellar motion similar to the natural microorganisms, with real-time AI navigation taking into consideration the blood flow, the geometry of the vessel and the vasculature of the tumour. Once received by the body, the

nanoswimmers would deliver targeted therapy, such as photothermal or chemotherapeutic, that would minimize systemic side effects common with traditional chemotherapy.

Figure 7 shows the quantum-AI nano-swimmer system architecture.

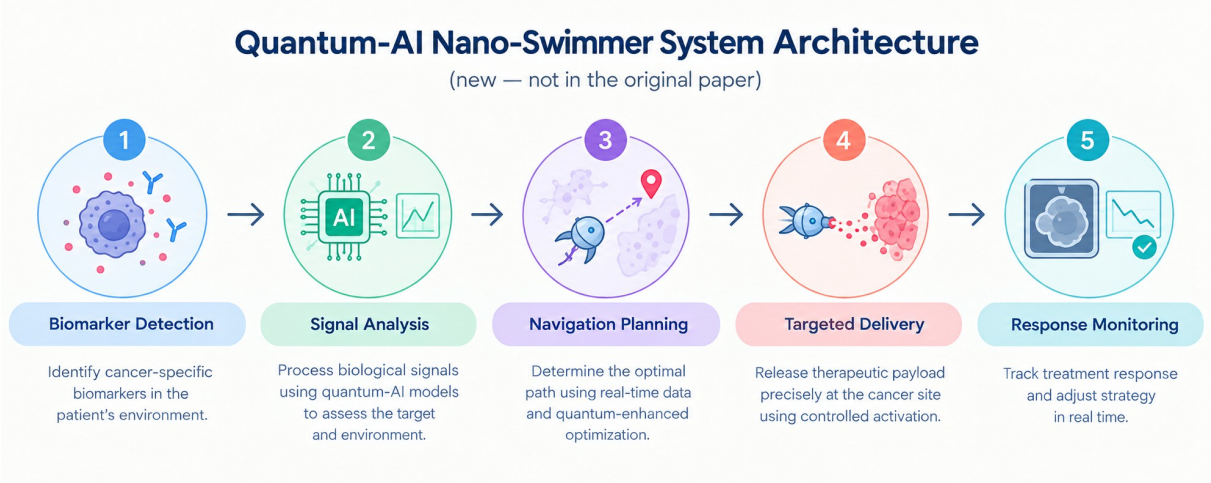


Figure 7. Quantum-AI nano-swimmer system architecture.

Table 2 summarizes this workflow across its five stages, from initial biomarker detection through post-treatment response monitoring.

Table 2. Quantum-AI nano-swimmer system workflow: five stages from biomarker detection to treatment.

Step	Component	Technology	Output
1	Biomarker Detection	Quantum Entanglement Sensors	Molecular signature map
2	Signal Analysis	CNN + QNN Classifier	Cancer type and stage
3	Navigation Planning	AI Path Optimization	Nano-swimmer route
4	Targeted Delivery	AI Nano-swimmer	Localized treatment
5	Response Monitoring	Quantum Imaging	Treatment outcome data

5 Research gaps and challenges

Despite the progress reviewed above, several structural challenges continue to limit the field's advance toward clinical deployment, summarized in Table 3.

Table 3. Key research gaps and challenges identified in AI and quantum-AI oncology research.

Challenge	Description	Impact
Quantum Hardware	High error rates, limited stable qubits (NISQ era)	Limits real-world QML deployment
Dataset Bias	Most studies use small, single-institution datasets	Reduced generalizability
Model Explainability	"Black box" deep learning offers low clinical trust	Hinders hospital adoption
Multi-Cancer Models	Most models target single cancer types	Misses co-occurring malignancies

Challenge	Description	Impact
Data Privacy	Sharing medical data across institutions raises GDPR and similar concerns	Constrains federated learning
Computational Cost	Deep learning requires GPU clusters unavailable to many institutions	Restricts equitable access to research

6 Future research directions (2025–2030)

A decade of advances is expected to bring six priority pathways to quantum-AI oncology research in the next five years, as summarized in Figure 8.

1. **Quantum Drug Discovery (30 percent priority):** Modeling protein-ligand binding interactions with historically "undruggable" targets using VQE and QAOA algorithms. Decades could be reduced to years for drug development for oncoproteins like KRAS.
2. **Liquid Biopsies with Quantum Enhancement (25 percent):** The quantum machine learning algorithm can identify exosomal biomarkers in blood at a very early stage of cancer, without any surgical procedures or invasive tests.
3. **Digital Twins (20 per cent):** HPC-QPU hybrid tumour simulations for tailor-made treatment planning, with real-time prediction of the treatment response in individual patients.
4. **Clinical use of Therapy with AI Nano-Swimmers (12 percent):** While awaiting biocompatibility and navigation studies, the framework proposed in this paper will be implemented.
5. **Federated Privacy-Preserving AI (8 percent):** distributed learning, where institutions don't share raw patient data, but is secured with quantum cryptography.
6. **Ethical AI and Regulation (5 percent):** Explainable AI and governance of quantum machine learning in clinical diagnostics.

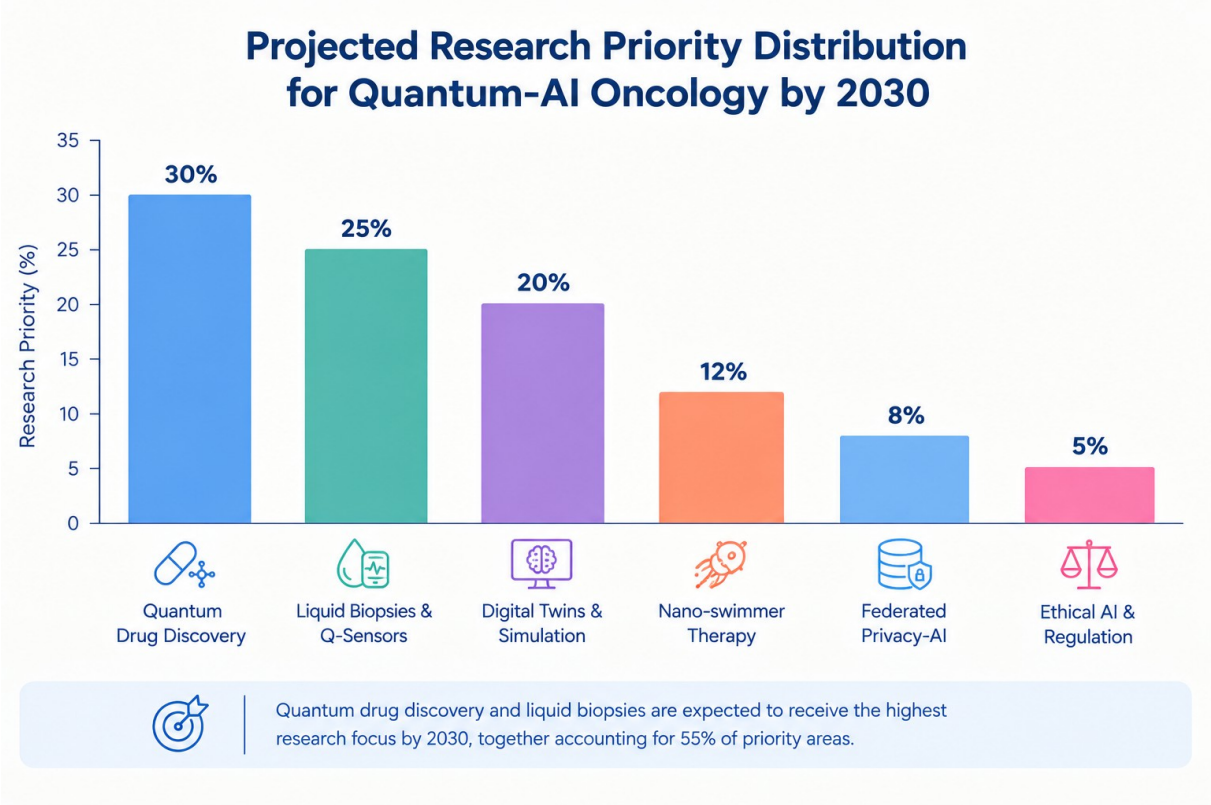


Figure 8. Projected research priority distribution for quantum-AI oncology by 2030.

7 Conclusion

This paper has demonstrated the confluence of artificial intelligence and oncology at the dawn of the quantum-AI era. From support vector machines' 97 percent accuracy in lung cancer screening (Rao and Arshad 2023) to convolutional neural networks' 99.8 percent accuracy in histopathology (Mohalder et al. 2021), cancer screening research employing AI is poised to exceed 99 percent accuracy in multiple cancer types through the integration of quantum-AI algorithms.

Three insights derive from this survey. First, convolutional neural networks comprise the most prominent class of AI algorithms for cancer screening and represent approximately 43.5 percent of all approaches considered. Second, quantum-AI specific studies have increased more than tenfold since 2015, with applications focusing on particularly challenging tumours, including pancreatic and prostate cancer. Third, the combination of quantum biosensors and AI-guided nano-swimmers presented in this paper provides a physically plausible, conceptual basis for the development of non-invasive, molecularly targeted cancer therapeutics.

The quantum-AI era for oncology is coming within a decade. As quantum-AI hardware, federated data validation platforms, and multi-cancer nano-therapeutic models emerge, systems akin to those postulated in this paper will begin to appear in clinical settings, fundamentally transforming cancer care.

References

[1] Abirami S, Chelliah BJ (2024). Early prediction of pancreatic malignancy by using deep learning techniques. In: *2024 Third International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT)*. IEEE, pp. 1–7. doi:10.1109/ICEEICT61591.2024.10718637

[2] Gottemukkala L, Kumar YJN, Teja USMP, Dhanraj NT, Nitish Y (2023). Prediction of liver abnormality using machine learning. In: *2022 OPJU International Technology Conference on Emerging Technologies for Sustainable Development (OTCON)*. IEEE, pp. 1–6. doi:10.1109/OTCON56053.2023.10113966

[3] Jha A, Verma G, Khan Y, Mehmood Q, Rebholz-Schuhmann D, Sahay R (2018). Deep convolution neural network model to predict relapse in breast cancer. In: *2018 17th IEEE International Conference on Machine Learning and Applications (ICMLA)*. IEEE. doi:10.1109/ICMLA.2018.00059

[4] Khademi M, Nedialkov NS (2015). Probabilistic graphical models and deep belief networks for prognosis of breast cancer. In: *2015 IEEE 14th International Conference on Machine Learning and Applications (ICMLA)*. IEEE, pp. 727–732. doi:10.1109/ICMLA.2015.196

[5] Li G, Luo J, Xiao Q, Liang C, Ding P, Cao B (2017). Predicting microRNA-disease associations using network topological similarity based on DeepWalk. *IEEE Access*, 5, 24032–24039.

[6] Mathews J, Joseph J, Reji R, Kamthe A, Deshmukh R (2023). Multi-disease prediction system using machine learning. In: *2023 6th International Conference on Advances in Science and Technology (ICAST)*. IEEE, pp. 330–334. doi:10.1109/ICAST59062.2023.10455036

[7] Mohalder RD, Sarkar JP, Hossain KA, Paul L, Raihan M (2021). A deep learning based approach to predict lung cancer from histopathological images. In: *2021 International Conference on Electronics, Communications and Information Technology (ICECIT)*. IEEE, pp. 1–4. doi:10.1109/ICECIT54077.2021.9641341

[8] Nooralli IM, Patil SB, Kulkarni G (2024). Predictive analytics for tongue diseases: A comparative study of deep learning models. In: *2024 International Conference on Innovation and Novelty in Engineering and Technology (INNOVA)*. IEEE, pp. 1–5. doi:10.1109/INNOVA63080.2024.10847037

[9] Piyarathna A, et al. (2019). Early prediction of lung diseases using CNN and CapsNet. *Kaggle dataset study*.

[10] Rao BD, Arshad M (2023). Early detection of lung cancer using machine learning technique. In: *2023 International Conference on Computer Communication and Informatics (ICCCI)*. IEEE, pp. 1–5. doi:10.1109/ICCCI56745.2023.10128389

[11] Regmi P, Verma S, Rani S (2025). Analysis 10-year cancer trends: Identifying key types with clustering. In: *2025 International Conference on Digital Innovations for Sustainable Solutions (ICDISS)*. IEEE, pp. 1–6. doi:10.1109/ICDISS68238.2025.11320588

[12] Singh RK, et al. (2020). Diagnosis of breast cancer using machine learning algorithms. *WBCD dataset study*.

[13] Song Q, Zheng YJ, Sheng WG, Yang J (2021). Tridirectional transfer learning for predicting gastric cancer morbidity. *IEEE Transactions on Neural Networks and Learning Systems*, 32(2), 561–574. doi:10.1109/TNNLS.2020.2979486

[14] Zhang WD, et al. (2019). Predicting invasive ductal carcinoma in breast histology images using CNN. *Kaggle dataset study*.